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Ecological Modelling 168 (2003) 217–231

ECOLOGICAL MODELLING

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# Optimization methodology for land use patterns—evaluation based on multiscale habitat pattern comparison

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**Abstract**

In this paper, the methodological concept of landscape optimization presented by Seppelt and Voinov [Ecol. Model. 151 (2/3) (2002) 125] is analyzed. Two aspects are chosen for detailed study. First, we generalize the performance criterion to assess a vector of ecosystem functions. This leads to a multidimensional analysis of the results of landscape pattern optimization. Second, we consider how these results relate to an existing landscape presented by some current land use maps. We apply an algorithm of pattern matching, which allows us to compare landscape patterns. With this tool we identify patterns in the study area, which are invariant during optimization and identify the relationships to recent landscape patterns known from data. As expected, the local optimization algorithm does not work well in certain situations that involve strong spatial interactions. We are presenting an example when global optimization cannot be efficiently performed in terms of local variables.



*Keywords:* Goal function; Dynamic spatial modeling; Decision support; Multi-criteria analysis

## 1. Introduction

Optimization of landscapes aims to identify landscape and land use patterns, which support certain ecosystem functions in an optimal way. The chosen performance criteria is then based upon the ecosystem functions, which are considered for optimization. In a former publication (Seppelt and Voinov, 2002), we presented a methodological framework on how to solve problems of landscape optimization based on grid-based spatially explicit ecosystem models. This framework enables us to study questions of optimal land use and landscape pattern configuration as a function of the performance criteria. In that case study, we focused on the assessment of nutrient outflow and farmers income given by economic yield minus production costs (fertilizers, labor, etc.).

We drew two major conclusions. First, for the given study area (Hunting Creek watershed, Maryland, USA), we can reduce the global optimization task to a local optimization problem, and consider every grid cell independently within the performance criteria and embed the results from the spatially explicit model into this algorithm of local optimization. Second, statistical analysis showed high correlation between optimization results and such spatial properties of the landscape as soil types, hydrologic conditions, elevation, exposition, slope, etc. However, that statistical analysis gave no explanation of the spatial

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doi:10.1016/S0304-3800(03)00138-8

configuration of patterns. No significant correlations could be derived and a principle component analysis could not assist in decreasing the state space. For this reason, we decided to extend our analysis to a more phenomenological study. The aim is to assess the approach presented previously with respect to practicability and reliability.

We took the following steps to address our goals:

- We derived a general formulation for ecosystem functions and aggregated several variables of an ecosystem function in a multidimensional performance criterion;
- We calculated the solutions for the optimization problem based on several different weighting schemes assumed for the multidimensional weighting vector;
- We compared the optimal land use patterns with some existing land use patterns documented in land use maps.

## 2. Study area and model description

### 2.1. Study area

We are considering the same mainly agricultural region in Southern Maryland, USA, as in our earlier paper (Seppelt and Voinov, 2002). We perform the analysis on the Hunting Creek watershed in Calvert County. The study area has a size of 22.5 km$^2$ and belongs to the drainage basin of the Patuxent River. The 2356 km$^2$ Patuxent catchment is one of the major tributaries of the Chesapeake Bay. The main land uses in the watershed are forest and agriculture. Rapid population growth, development and change in land use and land cover have become obvious features of the landscape, and more agricultural and forested land is now replaced by low density residential habitat. Soil in the area are well drained, mostly severely eroded soils that have a dominantly sandy clay loam to fine sandy loam subsoil (USDA, 1971, p. 76). The annual rainfall varies between 400 and 600 mm. For a detailed description of the study area, see Voinov et al. (1999a).

### 2.2. Spatially explicit agroecosystem model

The methodology presented by Seppelt and Voinov (2002) assumes a grid-based spatially explicit simulation model that is then treated by the landscape optimization tool. In the grid-based approach, we run process-based models in all the raster cells that represent the landscape. This is in contrast to approaches that use spatially lumped representations and aim to identify certain homogeneous regions (so called ecotopes or hydrotopes), for which a simulation is then performed (Krysanova et al., 1989; Krysanova and Haberlandt, 2002; Seppelt, 2000; Bicknell et al., 1997; Beven, 1997). The grid-based approach allows quasi-continuous modifications of the landscape, where habitat boundaries may change in response to socioeconomic transformations.

For the general description of the simulation model we consider the study region $R$ defined by a regular grid. Each cell is referenced by a column $i$ and a row $j$. Numbers of cells in each row and column may vary: $R = \{(i, j)|0 \leq n_i < i < N_i \leq N, 0 \leq m_j < j < M_j \leq M\}$. Here $N$ and $M$ define the size of the map that contains the study area. State variables of the model depend on time $t$ and on spatial location given by a grid cell $z \in R$. For instance, the habitat type shall be denoted by $H(z)$, the net photosyntheses by $\mathrm{NPP}(z, t)$, surface water baseflow by $Q_B(z, t)$ and the nutrient concentration in surface water $N(z, t)$.

The model has a hierarchical structure, which incorporates the ecosystem level unit model that is replicated in each of the unit cells representing the landscape. This habitat dependent information is stored in a parameter database, which includes initial conditions, rate parameters, stoichiometric ratios, etc. Although the same unit model runs in each cell, individual models are parameterized according to habitat type and georeferenced information for a particular cell. This design allows to simulate a variety of ecosystem types using a fixed model structure for each habitat type (Fitz et al., 1996; Voinov et al., 1999a).

Every cell model explicitly incorporates ecological processes that determine water levels or content of surface water and the saturated and unsaturated soil zone, plant production, nutrient cycling associated with organic matter decomposition and consumer dynamics. The general model for a habitat consists of a system of coupled nonlinear ordinary differential equations, solved with a 1-day time step. The model captures the response of vegetation to nutrient concentrations, water and environmental inputs. These processes are driven by hydrological algorithms for upland, wetland and shallow-water habitats.

The unit models in each cell are linked together by the exchange of material and information across space. Surface and subsurface hydrology define the horizontal fluxes. Those are driven by cell-to-cell head differences of surface water and saturated sediment water, respectively. Dissolved and suspended material (nutrients) is carried by water fluxes between cells.

A detailed documentation of the ecosystem model with respect to the hydrological processes was described by Voinov et al. (1999a). The development platform, the spatial modeling environment (SME) is described in Maxwell and Costanza (1997) and Maxwell (1995).

### 2.3. Validation

Validation of this complex model was performed using a stepwise approach. First, calibration of the hydrologic module was conducted against the USGS (1997) data for one gaging station on the watershed. The model was calibrated for the 1990 data and afterwards tested for 7 consecutive years (1990–1996). The results are in fairly good agreement with the data and may be considered as model verification, because none of the parameters have been changed after the initial calibration stage for 1990. No reliable data was available to calibrate the spatial dynamics of ground water. Nevertheless, the general hydrologic trends seem to be well captured by the model.

Once the watershed hydrology was mimicked with sufficient accuracy, the calibration of the water quality component was performed. Finally, the model was able to reproduce the trends of nitrogen concentration at the gaging station (USGS, 1995). In addition to the daily nitrogen dynamics we obtained a fairly good fit for the annual average concentration. For a detailed documentation of the validation results, see Voinov et al. (1999a).[1] Overall, the model seems to do a good job predicting the integral and distributed fluxes of nutrients over the watershed.

[1] On the Web page at http://giee.uvm.edu/PLM/HUNT further model output is presented.

### 2.4. Methodology of spatially explicit landscape optimization

Landscape optimization based on spatially explicit models aims to identify habitat patterns so that certain designated ecosystem functions are optimized. The scope of recent publications on optimization of landscape patterns varies in terms of the considered problem as well as of the methodology applied. Spatial management problems on a sustainable use of forest (Loehle, 2000; Tarp and Helles, 1997) or agricultural region (Nevo et al., 1993; Seppelt, 2000; Makowski et al., 2000) use nonlinear optimization and stochastic variation approach for optimization. The mathematical structure varies from exponential growth to coupled non-linear differential equations. Additionally, applications of optimization approaches for habitat suitability assignment are presented by Bevers et al. (1997). Hof and Bevers give an overview of most recent advances on this field in Hof and Bevers (2002).

These authors develop an excellent algorithmic solution to the given problem. The solutions depend on scale, spatial database (vector or grid) and strength of spatial interaction of connected habitats. However, no general approach of optimization based on spatially explicit models can be found in recent literature.

The methodological framework, presented in Seppelt and Voinov (2002), builds upon the grid-based approach of SME, and allows quasi-continuous changes of land use habitats. However, the requirements of this approach can be applied to different spatial explicit model, as long as a grid-based approach is chosen.

Identification of optimum land use patterns depending on a given performance criterion $J$ (see below) leads to a very complex task. For this reason, we distinguish between local and global optimization problems. The global optimization task is discussed by Seppelt and Voinov (2002) in detail. It requires iterative gradient-free algorithms. However, in some cases most of the variability of the optimization process is captured by the local solution, which is in fact the starting point for the global optimization task.

This local optimization problem is solved as follows:

1. Control variables, such as land use, fertilizer input, etc. are identified. Continuous variables, like the

amount of fertilizer application, are discretized. In terms of a combinatorial problem all possible combinations of the controls are set up. Based on this setup of the control variables, input maps are defined with an identical value of the control vector for every controllable cell (homogeneous land use).
2. These maps are fed into the spatially explicit model. Simulation runs are performed for each of these input maps.
3. For every simulation run resulting maps are stored for those model variables, which are included in the performance criterion. These may be spatial variables, stored as maps.
4. Based on spatial variables, which define the performance criterion, the optimal values of control variables are derived by sorting through all the combinations stored for every grid cell.
5. The final spatial simulation is performed based on the locally optimal control maps.

## 3. Assessment of ecosystem functions

For a more general analysis, we want to expand the number of environmental factors that we take into account. We focus on the following ecosystem functions, which can be quantified by certain state variables, or derived from a set of state variables assumed in the ecosystem model:

- We consider basic ecosystem productivity given by the total rate of net primary production $\mathrm{NPP}(z)$ ($\mathrm{kg/m^2}$). This also indirectly represents the retention capability of nutrients (nitrogen) and the uptake of greenhouse gas $CO_2$, and has been identified as an important indicator of overall ecosystem services provided by a land use type (Costanza et al., 1997).
- Nutrient outflow out of a grid cell with horizontal flows of surface and subsurface water: $N(z)$ ($\mathrm{kg/m^2}$). This can be interpreted as overconsumption of retention capability of the ecosystem.
- Another variable that we would want to take into account is the amount of surface water baseflow in the streams, $Q_B(z)$ ($\mathrm{m^3}$ per day) calculated as the total of the 50% of the minimal daily flow values. This identifies how land use change effects the hydrologic conditions in the area. In most cases lower baseflow is associated with increased vulnerability to drought and peak flooding, which makes it an important characteristic of the landscape and the health of associated ecosystems.

Additionally the following economic aspects are considered. The economic yield $Y(z)$ of an agricultural site $z$—farmers' income—can be calculated as the difference of market price $p_c(c)$ for the harvested biomass $B(z)$ of crop $c$ minus the production costs $p_f$ given by the cost of fertilizers applied: $Y(z) = p_c(c)B(z) - p_f F(z)$.

For these ecosystem functions the simulation model dynamically calculates the required state variables. We may further expand the number of functions that we account for in the performance criterion. For example, it would make perfect sense to include the value of land used for recreation or for housing, in which case agricultural or forested habitat will become residential. However, methodologically it will be the same and we do not want to make the calculations any more complex at this time.

A performance criterion $J$ aggregates state variables, which represent the considered ecosystem functions. For optimization purposes we need to define the performance criterion, which aggregates the above listed three ecological variables and the economic variables into a scalar function. However these variables are incomparable in terms of units: we cannot add dollars of yield to kilograms of primary productions to cubic meters of water flow. To match the units among the different elements in the performance criterion, we introduce a vector of weighting factors $\lambda_x$. $N$ has to be minimized, while all other variables are to be maximized. This leads to the following performance criterion:

$$\begin{aligned} J(z) &= Y(z) + \lambda_{Q_B} Q_B(z) + \lambda_{\mathrm{NPP}}\mathrm{NPP}(z) - \lambda_N N(z), \\ J(z) &= Y(z) + (\lambda_{Q_B}, \lambda_{\mathrm{NPP}}, -\lambda_N) \cdot \begin{pmatrix} Q_B(z) \\ \mathrm{NPP}(z) \\ N(z) \end{pmatrix} \\ &= Y(z) + \vec{\lambda} \cdot \vec{x}(z) \end{aligned} \tag{1}$$

Compared to the performance criterion used in Seppelt and Voinov (2002), we now have a vector of weights $\vec{\lambda} = (\lambda_N, \lambda_{Q_B}, \lambda_{\mathrm{NPP}})^T$. The specification of $J$ is a multidimensional problem. Our other problem is that the performance criterion is formulated in terms of global landscape conditions: we are concerned with the water quality and quantity at the outlet of the drainage area, we are considering the total NPP of the area and the total profits from the agricultural crops. However, to apply the localized spatial optimization algorithm, we need to formulate these goals in term of local variables that can be traced for each individual cell. As we will see below this may not be always possible.

The local performance criterion is quite identical to the global one for the economic part and for NPP. Both these variables are additive, therefore, if we maximize NPP or agricultural profits for each individual cell, we will be also maximizing the total profit and total NPP from the watershed. Accounting for water quality and quantity is not that straightforward, since these variables are not additive and undergo much change and transformation on their way between the localite (individual cell) and the drainage point of the watershed. Yet, for now, we will assume that the water quality globally can be desrcibed by the water quality in each cell and, similarly, that the baseflow at the drainage point (calculated as the total of the 50% of the minimal daily flows) is related to the total of the less than average surface water stages in cells.

In the following, we will analyze how the optimization results are influenced by the different weighting of the ecosystem functions in the performance criterion. Essentially the weights in this formulation are the dollar values that we assign to the different ecosystem functions.

## 4. Landscape pattern optimization

### 4.1. General results for optimal land use patterns

In the first analysis, the optimization results can be investigated using the habitat distribution of the entire investigation area. If we use only one dimension of the vector of weights $\vec{\lambda}$ in the performance criterion, these results can be summarized as follows.

Neglecting all ecological concerns and focusing on economic profits only, $\vec{\lambda} = 0$ the optimum land use is to plant soybean (70%) and corn (30%). The entire study area changes to agricultural use only.

Introducing ecological aspects in the performance criterion makes forest an optimum habitat. In detail:

- Focusing on NPP, forest (70%) and corn (30%) become the dominant land use;
- Prioritizing N-output, a distribution of land use assuming 70% forest and 12% soybean and 12% corn is most efficient;
- Considering baseflow, $Q_B$, most important, one would expect forest to cover most of the area, since it seems to be the kind of habitat that is most favorable to increase water retention, cf. for example, Pattanayak and Kramer (2001). However, our optimization results with fallow dominating the landscape, which is quite suspicious.

Two questions result from this preliminary analysis:

1. How do these results change if scenarios of assessment are combined, e.g. if the weights of ecosystem function values given by $\lambda$ are modified?
2. Which regions are effected by a change of land use and how is this related to the current data for land use distribution in the study area?

The second step in analysis of the results is the estimation of optimal land use distributions as a function of different weighting schemes. This requires a broad range of optimization runs with varied $\lambda$-values. This can be performed without much computational effort due to the separation of local and global optimization methodology (Seppelt and Voinov, 2002).

A graphical representation of the habitat distribution as a function of the multi-dimensional weighting space $\vec{\lambda}$ is hardly possible. Nevertheless, Figs. 1 and 2 give an idea about how the changes in the optimum land use distribution in the Hunting Creek area are driven by different weighting schemes. Fig. 1 shows how optimization results of habitat distributions change with a variation of the weights $\lambda_N$ (plot a), $\lambda_{Q_B}$ (plot b) and $\lambda_{\mathrm{NPP}}$ (plot c). All three figures support the above-mentioned general conclusion, that forest becomes an important part of the landscape, if ecological issues are taken into account in the performance criterion. Depending on the ecosystem function stressed by the weighting in the multi-dimensional performance criterion, for the remaining area, different habitat types are chosen. Focusing on net primary production corn is an important habitat. Corn and and wheat are chosen, if nutrient outflow is considered in the goal function.

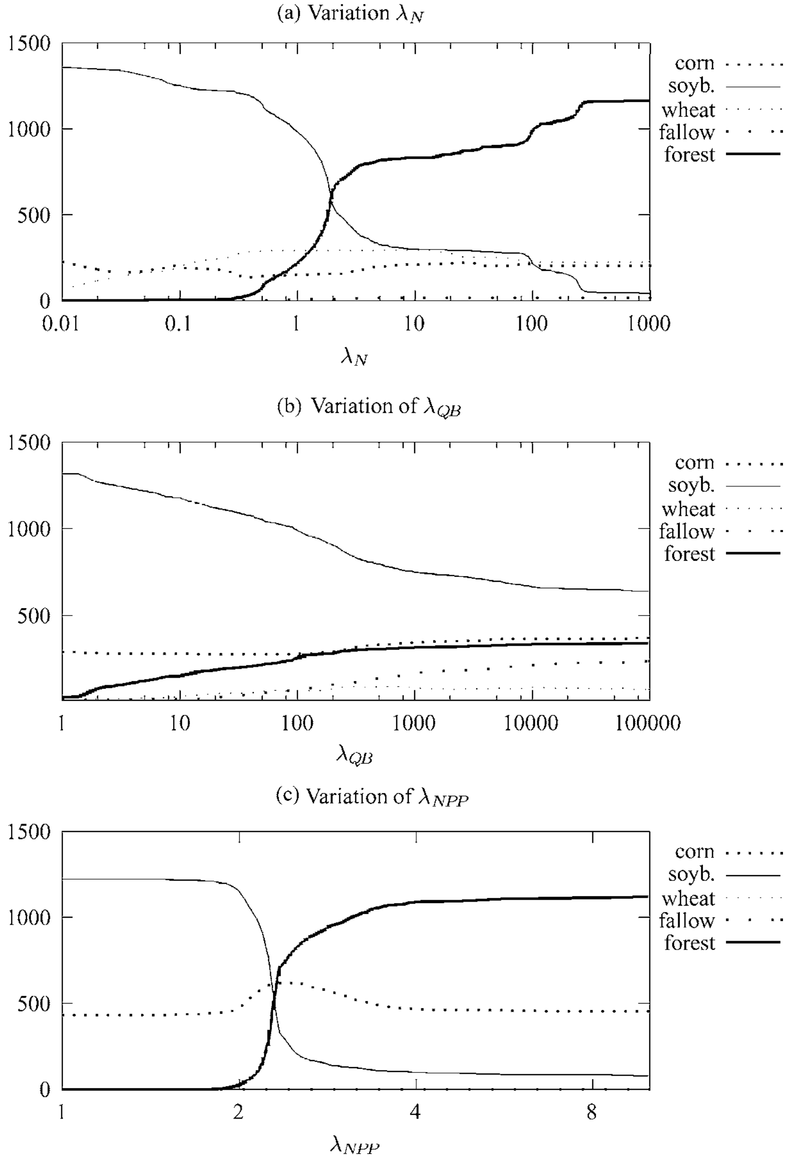


Fig. 1. Optimum land use distribution as a function of weighting coefficients $\lambda_N$, $\lambda_{Q_B}$ and $\lambda_{\mathrm{NPP}}$. Plot (a) shows the response of the optimum land use distribution to a variation of $\lambda_N$ ($\lambda_{Q_B} = \lambda_{\mathrm{NPP}} = 0$), (b) the response to $\lambda_{Q_B}$ ($\lambda_N = \lambda_{\mathrm{NPP}} = 0$) and the lower plot (c) to $\lambda_{\mathrm{NPP}}$ ($\lambda_N = \lambda_{Q_B} = 0$).

Note that for the *x*-axis a logarithmic scale is chosen. We get different results of optimum land use distribution changing $\lambda_N$ and $\lambda_{Q_B}$ within five orders of magnitudes. Whereas the optimized land use distribution changes with a variation of $\lambda_{\mathrm{NPP}}$ in the interval $\lambda_N = 1, \ldots, 10$. These results can be interpreted as a sensitivity analysis of a parameterized multi-criteria analysis. This could provide a basis to choose weighting scenarios for more detailed studies.

Fig. 2 shows three similar graphs. For selected values of $\lambda_{\mathrm{NPP}}$ and $\lambda_{Q_B}$, the land use distribution is plotted as a function of $\lambda_N$. Forest is an important habitat in the landscape covering more than 50%, if net primary production or base flow is considered

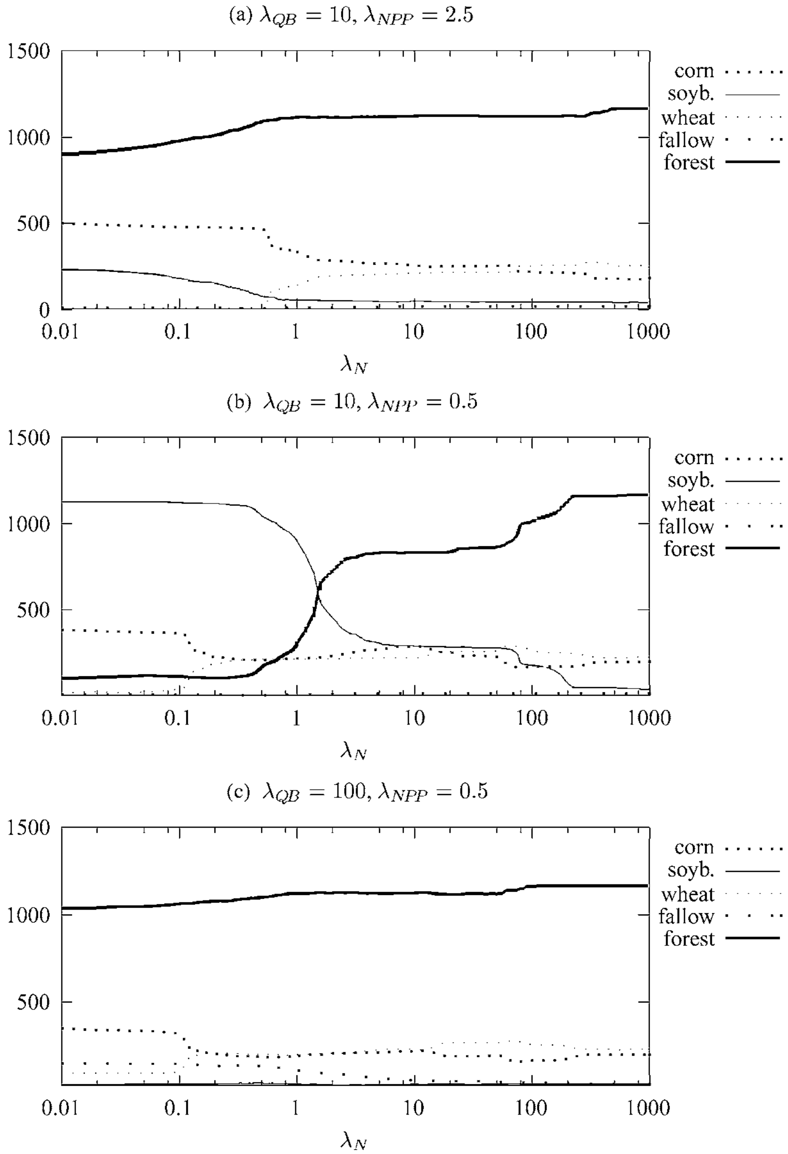


Fig. 2. Optimum land use distribution as a function of weighting coefficient $\lambda_N$.

in the performance criterion. Also fallow may be an optimal land use, if baseflow is stressed and nutrient outflow is neglected.

Based on the general behavior of the model derived from the sensitivity analysis in Fig. 1, one could hardly infer the plots presented in Fig. 2. The general conclusion is that, although the performance criterion is simple and linear, there are essentially nonlinear changes in the optimal landscape patterns. We know from former work that these patterns are caused by a highly complex network of spatially distributed parameters and processes in the underlying simulation model.

### 4.2. Scenarios of optimized land use patterns

Next we have selected six weighting schemes for more detailed analysis. Table 1 lists the selected values for the weighting vector $\vec{\lambda}$ in the upper part. Note

Table 1
Definition of weighting scheme $\vec{\lambda}$ for optimization scenarios 1–6 (upper part of table) and aggregated optimization results of the control variables land use and fertilizer input

| | Scenario 1 | Scenario 2 | Scenario 3 | Scenario 4 | Scenario 5 | Scenario 6 | Unit | References |
|---|---|---|---|---|---|---|---|---|
| Specification of performance criterion weights $\vec{\lambda}$ | | | | | | | | |
| $Y(z)$ | >0 | 0 | >0 | >0 | >0 | >0 | | $Y(z) = 0$, >0[a] |
| $\lambda_N$ | 0.05 | 0.01 | 1.5 | 0.0 | 50.0 | 0 | | |
| $\lambda_{\mathrm{NPP}}$ | 0.0 | 0.5 | 0.5 | 0.0 | 2.5 | 2.5 | | |
| $\lambda_{Q_B}$ | 0.0 | 100 | 10 | 100000 | 1000 | 0 | | |
| Resulting control variables | | | | | | | | |
| Percentage of land use $H(z)$ | | | | | | | | |
| Corn | 10.5 | 21.1 | 13.7 | 22.4 | 13.3 | 37.8 | % | |
| Soybean | 79.2 | 1.8 | 36.8 | 38.6 | 1.9 | 12.8 | % | |
| Wheat | 9.9 | 5.7 | 13.2 | 4.4 | 14.2 | 0.1 | % | |
| Fallow | 0.1 | 9.1 | 0.8 | 14.2 | 0.3 | 0 | % | 70.9%[b] |
| Forest | 0.2 | 60.5 | 35.5 | 20.5 | 66.9 | 49.5 | % | 29.1%[c] |
| Applied fertilizer | | | | | | | | |
| $\sum F(z)$ | 5.58 | 2.14 | 2.79 | 2.61 | 0.65 | 4.62 | g/m$^2$ | |
| Resulting state variables | | | | | | | | |
| $\sum$ NPP | 148 | 635 | 442 | 265 | 699 | 667 | g/m$^2$/year | 650 g/m$^2$/year[d] |
| $\sum N(z_0)$ | 2.05 | 0.84 | 0.91 | 2.24 | 0.37 | 0.69 | g/m$^2$ | |

Last column shows recent distribution of agricultural and forest area and literature values for selected state variables of performance criterion.
[a] $Y(z) > 0$ denotes $Y(z)$ is considered in the performance criterion as defined in Eq. (1). $Y(z) = 0$ denotes economic yield is neglected for optimization.
[b] Total agricultural area, Hunting Creek, 1990.
[c] Forest Area, Hunting Creek, 1990.
[d] cf. (Jørgensen et al., 2000, Table 2-202).

that with the exception of scenario 2, all economic elements of the weighting vector are set according to recent prices for crops and prices of fertilizer. This means that optimization of ecosystem function can be interpreted in economic values. In scenario 2, $Y(z)$ is neglected, e.g. set to zero. With this scenario we take a closer look at the interrelationship between the three ecosystem functions in the optimization results with respect to the attributes of the study area, e.g. soil properties, elevation, etc.

Table 1 summarizes the optimization results in an aggregated way, listing habitat distribution and the total amount of fertilizer applied in each of the nine optimal scenarios. For comparison, recent land use (1990) shows 70% forest and 30% agricultural habitats for all controllable cells, that is open water, rural and urban areas are neglected in the comparison.

These optimized habitat maps and optimal fertilizer maps are now fed into the Hunting Creek model and full spatially explicit simulations on these so-called optimization scenarios are run. We simulate a vegetation period of one and a half years (551 days). Fertilizers are applied during the vegetation period at the times recommended by best management practices (Voinov et al., 1999b). Results can be then analyzed with respect to spatial properties as well as with respect to the overall performance measures, such as total nutrient outflow from the entire watershed.

In addition, we can compare the results with some of the information available from other published sources, cf. for instance, the Ecotox database (Jørgensen et al., 2000). It was encouraging to find that most of the results of our simulation, like NPP, have the same order of magnitude as reported in literature, cf. Table 1 lower part.

Surface water and nutrient concentration in the basin outlet cell are important aggregated indicators for numerous spatial hydrologic processes and for the nutrient cycle. The drainage cell connects to the Patuxent River, which then drains into the Chesapeake Bay. To analyze the nutrient balance, three scenarios are chosen for Fig. 3: Scenarios 1, 2 and 4. These scenarios

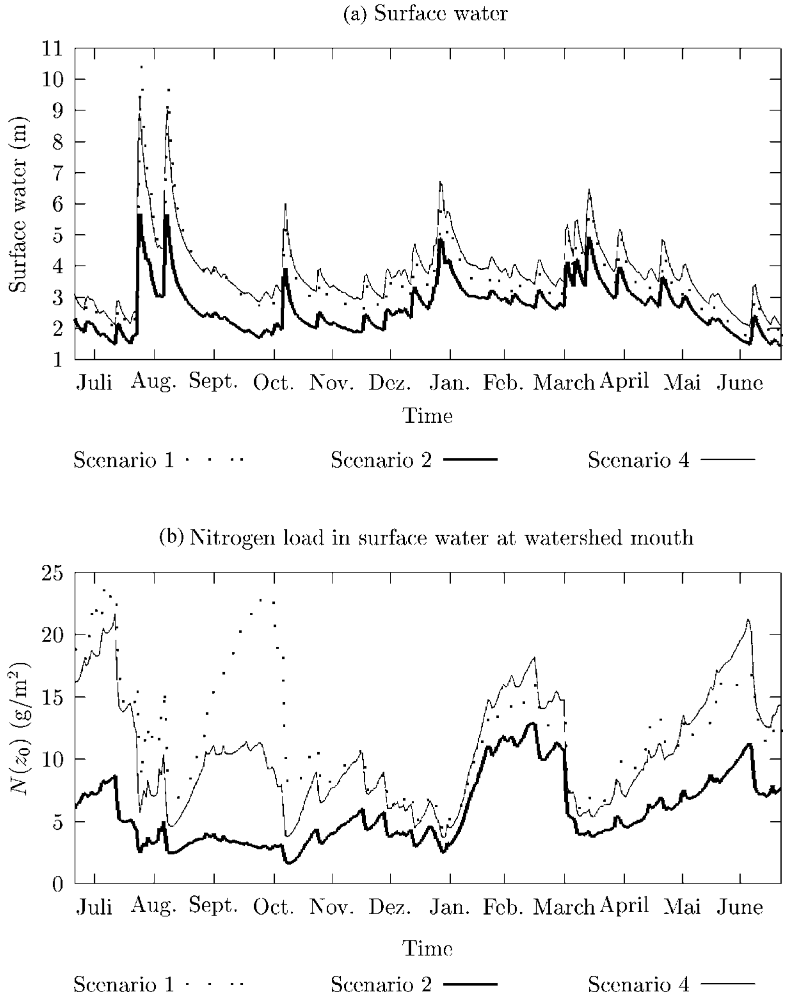


Fig. 3. Time series of surface water level (plot a) and nitrogen load (plot b) both taken at the watershed outlet cell $z_0$. Results from the scenarios 1, 2 and 4 display the overall variation of all six scenarios.

cover the range of variation for all scenarios. The figures display the last year of simulation from July to June, $t \in [186\text{d}, 551\text{d}]$.

In the upper plot (Fig. 3(a)), the surface water level is displayed. The resulting simulations based on optimization scenarios 1 and 4 show water levels twice as high as the result from scenario 2. Considering the chosen weight, cf. Table 1, this result is somewhat contradicting to the optimization goal. A higher value for $\lambda_{Q_B}$ should result in a higher baseflow, which should result in a higher average water level and lower peaks of the surface water level in the outlet cell.

We have then hypothesized that it is most likely that by maximizing the amount of surface water in each cell, we were actually decreasing the baseflow, since more water on the surface means more water available for immediate runoff, higher evaporation, and as a result less water in saturated layer, that feeds the stream network during dry periods. We tried to fix the performance criterion to make it better represent the baseflow in the stream. Instead of surface water in the cells, we included the amount of water infiltrated.

This time we did get the displacement of corn by forest in the landscape (Fig. 4), but further on, with

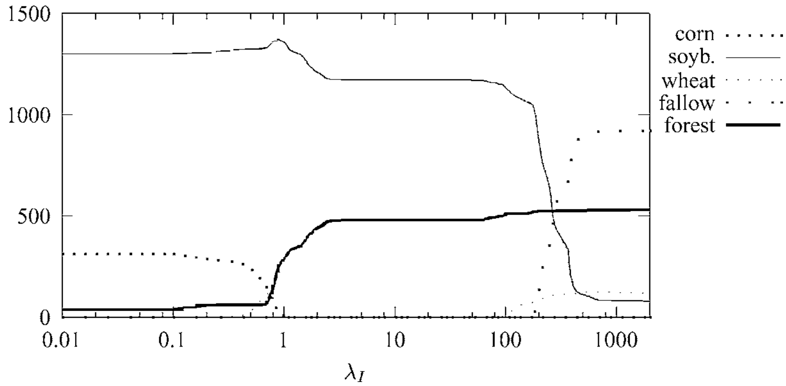


Fig. 4. Optimum land use distribution as a function of weighting coefficient $\lambda_I$ of the performance criterion adding yield and accumulated infiltrated water.

even higher weights attached to the baseflow, we find that it is fallow that displaces soy beans, not forest! Even though the infiltration coefficient per se is 3 times higher for forests, than for fallow, apparently now the infiltration capacity starts to play the most important role. The amount of water infiltrated depends not only upon the infiltration rate, but also on the amount of pore space in the unsaturated zone, that can take water in the infiltration process. For fallow we assumed evaporation from unsaturated layer 10 times higher than in forests. As a result we get more infiltration capacity in fallow, and, hence, more water infiltrated.

If we calculate baseflow globally we still achive the highest results for moslty forested landscapes. Therefore, we should conclude, that optimization for baseflow is not achieved with the chosen methodology of local optimization, e.g. simplifying the spatially explicit problem. There seems to be no good way to express baseflow (a global feature) in terms of some local variables and processes. Processes that show high spatial interaction are hard to treat with this local optimization methodology, cf. Seppelt and Voinov (2002). Performance criteria and optimization algorithms need to be formulation on a global or at least regional scale.

On the other hand, minimization of nutrient outflow is achieved by local optimization. Fig. 3b displays the time series of the nitrogen load in the outlet cell. Scenario 1, which almost neglects any ecological aspects, results in higher nutrient concentration. Scenarios 2 and 4 result in lower nitrogen concentrations. Note that this is an outcome of spatial allocation of land use type only, the climatic conditions (most importantly precipitation and atmospheric N-input) as well as fertilizer application are constant, cf. Table 1.

These both results may sound contradictory, since nutrient flow is strongly related to hydrology. Apparently nutrient flow is more spatially buffered and has less spatial variability, so the local performance criterion captures the effects that play the most important role globally.

Fig. 5 gives an overview of the 1990 land use in the Hunting Creek region. The watershed area is shared between urban, rural, open water, forest and agriculture habitats. No distinction for different crops is made in that map. Fig. 5 also offers detailed maps of a small region near the creek. These areas near rivers and creeks were identified as crucial in terms of optimization for the nutrient balance in the region as described by Seppelt and Voinov (2002).

The map from Scenario 1 shows that neglecting ecosystem functions and ecological impacts of agricultural production results in an optimum with agricultural habitat occupying the entire study area. All other weightings result in more heterogeneous optimal landscape patterns. Two issues should be noted. First, cells selected for agricultural production show similar patterns independent of the chosen weighting scheme. Only the crop variety planted depends on the ecosystem function(s) chosen in the performance criterion. Second, the cells allocated for agricultural production seem to be the same, perhaps shifted by some grid cells, as in the current land use for agriculture

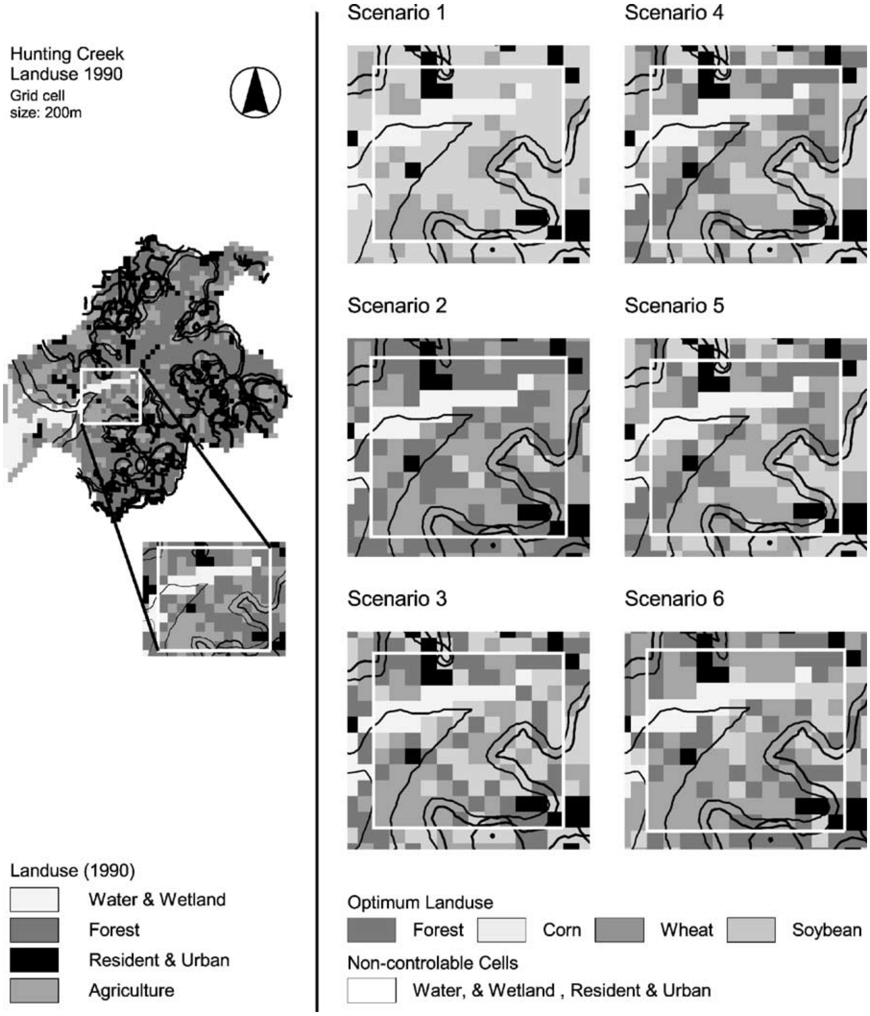


Fig. 5. Resulting land use patterns of the six optimization scenarios.

in Hunting Creek. One may derive the hypothesis that the history of agricultural production in Hunting Creek developed towards a somewhat optimal landscape. The question is raised how one can compare the recent land use with the results derived from the optimization procedure.

## 5. Multi-scale analysis of landscape patterns

The comparison of landscapes required the comparison of habitat patterns. Two approaches of pattern comparison come to mind, if one considers grid-based maps with discrete attributes. The coarsest approach is to compare the distribution of habitats in the entire area. This neglects any spatial patterns. The finest approach is to compare cell by cell, or pixel by pixel and to count the number of matches. This may be much too strict as patterns may appear transposed, rotated or slightly shifted in both maps. We would still call these landscapes similar if we were visually comparing them. What we need is a distance measure, which allows a merger of both approaches.

### 5.1. Distance measure of discrete maps

Habitat maps show discrete attributes, for instance soybean (1), corn (2), urban (3), etc., which may be summarized by an integer attribute $H(z) \in \{1, 2, \dots\} = S$. The number of attributes of classes—here habitat types—is given by $|S|$.

The basic idea for the comparison of two habitat maps[2] $H_1$ and $H_2$ goes back to the multi-scale approach from Costanza (1989). Using a moving window with the edge length $w \geq 1$ the number of cells in the window, belonging to a certain class $i$ is compared for each habitat map $H_1$ and $H_2$. Let us denote this moving window at cell $z \in R$ and the width and length $w \geq 1$ by $U_w(z)$.

Let $g_i(H \cap U_w(z))$ denote the number of cells with the attribute $i$ in a window $U_w(z)$ at location $z$ on map $H$. Then

$$\rho_w(H_1, H_2) = \frac{1}{2}\frac{1}{|R|}\frac{1}{|H_1 \cap U_w(z)|} \cdot \sum_{z \in R}\sum_{i=1}^{|S|} |g_i(H_1 \cap U_w(z)) - g_i(H_2 \cap U_w(z))|$$

defines a function which measures the distance between map $H_1$ and map $H_2$ using a moving window of size $w^2$. $|\cdot|$ denotes the size of considered map in the argument given in numbers of grid cells.

Function $\rho_w$ is very intuitive and has all the essential features of a distance measure:

1. $\rho_w(H, H) = 0$ for an arbitrary $w \geq 1$: The distance between two identical maps is zero.
2. If $\rho_w(H_1, H_2)$ is divided by $|R|$ the function is normalized to unity for entirely different maps: $\rho_w(H_1, H_2) = 1$ for each $w \geq 1$ if and only if $H_1(z) \neq H_2(z)$ for all $z \in R$.

   Setting the maximum value of $\rho_w$ equal to unity is an arbitrary definition. Neglecting this normalization is a reasonable choice, too. This might allow to compare maps with different shape. However, using the normalized value, the following properties of $\rho_w$ become valid.
3. $\rho_1(H_1, H_2)$ denotes the difference between $H_1$ and $H_2$ in grid cell scale. This means $1 - \rho_1$ is the fraction of cells which are identical.
4. Let $L$ define the maximum diameter of the study area or the given map $H$: $L = \max \operatorname{diameter}(H)$. The diameter is given by length of the largest of all possible cross-sections of a map. Then $\rho_\infty(H_1, H_2) = \rho_L(H_1, H_2)$ denotes the distance if the moving window covers the entire study area $R$. In that case the distribution of attributes in the maps $H_1$ and $H_2$ is compared. That means that $1 - \rho_\infty$ denotes the fraction of attributes with an equal distribution in both maps.

For an overall assessment of the map distance $\rho(H_1, H_2) = (1/L)\int_0^L \rho_w(H_1, H_1)\,\mathrm{d}w$ may be calculated. The upper limit of integration is given by the maximum diameter of the study area. A second integrative measure derived from $\rho_w$ is $\rho_0(H_1, H_2) = \min_{w=1,\dots,L}\rho_w(H_1 H_2)$ together with the $w_0$-value, for which $\rho_w$ equals its minimum. These two values indicate the similarity or distance of two maps $H_1$ and $H_2$ as well as the scale or distance at which most patterns fit.

Additionally, one can prove that $\rho$, $\rho_\infty$, $\rho_0$ and $\rho_1$ are distances measured in a mathematical sense. It holds true, that

(i) $\rho(A, A) = 0$

(ii) $\rho(A, B) \neq 0 \Leftrightarrow A \neq B$

(iii) $\rho(A, C) \leq \rho(A, B) + \rho(B, C)$

### 5.2. "Correlation" analysis of optimal landscape patterns

We now apply this approach of map comparison to the results of the landscape optimization scenarios 1–6. Similar to correlation analysis, Table 2 displays the $\rho_0$-values and the window sizes $w_0$, for which $\rho_w$ is minimal.

This clearly shows that habitat maps from scenarios 1 are different from all other habitat maps in terms of their likelihood to other maps ($\rho_0 > 0.65$). Compared to scenarios 2–6 this scenario is characterized by very low values for ecosystem functions. However, minimum values of $\rho_w$ are reached for $w = 3, \dots, 9$. To explain this we should recall that non-controllable cells presenting urban, open water and rural areas are

[2] We denote a map or part of a map with a capital lettter $H$. The attribute of a certain grid cell $z$ is denoted by $H(z)$.

Table 2
Map comparison of optimum habitat maps $H$ for the scenarios 1–6 and comparison with recent land use

| | Recent land use | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| 1 | 0.59 (3) | | | | | |
| 2 | 0.1 (9) | 0.72 (7) | | | | |
| 3 | 0.31 (5) | 0.35 (9) | 0.38 (27) | | | |
| 4 | 0.46 (6) | 0.37 (52) | 0.41 (9) | 0.26 (24) | | |
| 5 | 0.04 (15) | 0.66 (5) | 0.14 (38) | 0.32 (6) | 0.54 (9) | |
| 6 | 0.17 (7) | 0.65 (3) | 0.19 (57) | 0.34 (33) | 0.41 (9) | 0.27 (56) |

The table displays the $\rho_0$-values of two optimized habitat maps $H_i$ and $H_j$ ($i = 1, \ldots, 6$; $j = 1, \ldots, i$) and the associated $w_0$-values. The table is to be read like a correlation-matrix, see text.

also taken into account for map comparison. In this case spatial patterns of these cells dominate the map comparison values.

All other comparisons lead to smaller $\rho_0$-values. In these cases the $w_0$-value is a good indicator by what may be causing this similarity. If $w_0$ is close to the study area size $L = 58$, similarity is mainly caused by the agricultural habitat distribution over the entire study area. Smaller values of $w_0$, e.g. for comparisons of scenarios 2 versus 9, 3 versus 8 and 6 versus 9 show that certain more local landscape patterns cause similarity. Comparing these results with weighting schemes of $\vec{\lambda}$ in Table 1 we arrive at a surprising result: The $\lambda$-vectors for these scenarios are not close to each other in the three-dimensional weighting space. This again makes clear that the underlying processes incorporated into the spatially explicit simulation model are highly nonlinear with respect to dynamics and to spatial dynamics of material fluxes.

With the developed map distance measure we can answer the question raised in the previous section. How similar is the recent land use compared to the maps resulting from the optimization procedure? Table 2 shows map distance measures for the recent land use and the maps resulting from the optimization scenarios. Note that in this application of the distance measure only the habitat types for forest, agriculture, open water, urban and rural are taken into account to match the categories on the underlying data set of the 1990 land use map.

As expected the optimized map from scenario 1 is different from the 1990 land use map ($\rho = 0.59$). However, some similarities are identified for a 3-cell-wide moving window. Results from scenarios 3 and 4 seem to be closer to the 1990 land use map. The maps resulting from the optimal scenarios 2 to 4 are almost identical to the 1990 map. The similarity is caused by similar patterns at the scale of 5- to 7-cell-wide windows. This proves the hypothesis from the previous section: The resulting maps from the optimization are similar to the recent land use map. Note that this holds only for a distinction between aggregated agricultural and forest cells as this is the level of detail the data land use map offers.

## 6. Discussion

There are two major results of this study. First, on a global scale the optimization problem based on a multidimensional performance criterion leads to optimum land use patterns, which support certain ecosystem functions. These patterns can be then studied as a function of weighting coefficients in the performance criterion. Second, with an adequate map comparison methodology we can show, that certain patterns are invariant to different weightings of ecosystem functions in the performance criterion.

One may summarize these results qualitatively in the following way, which may be interpreted as a multistage decision making process.

1. If only economic considerations are taken into account in the performance criterion, cells that are optimal for agricultural production are identified;
2. If ecosystem functions are considered (one of $\lambda_{\mathrm{NPP}}, \lambda_{Q_B}, \lambda_N > 0$) less fertile sites and cells crucial for the regional nutrient balance are identified;
3. Depending on particular weighting schemes for $\lambda_{\mathrm{NPP}}, \lambda_{Q_B}, \lambda_N$ a certain combination of fertile and less-fertile cells are allocated for agriculture;

4. The remaining cells are allocated for forest habitats.

These studies may be viewed as model experiments in spatial change in land use allocation in the landscape. In this context, it is interesting to see that some optimized habitat maps are fairly close to maps of the existing landscape. We can conclude that in some sense the existing landscape in the Hunting Creek watershed is optimal, at least in terms of some of the assessment scenarios.

The results of this paper speak in favor of the earlier statement (Seppelt and Voinov, 2002) that the developed methodology gives robust optimization solutions based on complex ecosystem models. They extend the previous analysis for multidimensional performance criteria and show how to identify important regions or groups of cells, which support certain ecosystem functions. However, in this study, we identified processes that could not be handled within the localized optimization methodology. Two directions for further research can be derived from those results. First, criteria are to be defined that characterize sub-models with their appropriate spatial optimization strategy. Second, methodology for global or at least regional scale spatial optimization are to be developed or improved.

As the modeling and optimization approach presented incorporates aspects of topology and connectivity of cells, statistical analysis applied to multidimensional spatially explicit models is limited. The presented methodology of map comparison extends analysis of multivariate statistics. With the use of landscape pattern comparison we are able to show how much optimization results differ in terms of local patterns for global (whole watershed) land use distribution. Additionally, invariant patterns can be identified and the spatial scale of the invariant patterns can be quantified.

This may lead to further applications. One important issue is the application of the multi-scale landscape comparison methodology in model validation and calibration tasks. Based on historical land use maps one may try to identify the associated weighting of ecosystem functions. Although this problem will have multiple solutions, it could be a valuable explanation of different land use and management strategies.

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